Context-Enhanced Information Fusion for Tracking Applications

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***Abstract*—Over the last decade, context has become a key source of information for tracking problems. Context inference allows refining sensor modeling and target dynamics as well as the creation of motion constraints according to the physical and operational conditions of the scenario. This work presents two example applications: indoor and inland waterway navigation where the context information is employed to reduce the uncertainty of the tracking and enhance the navigation solution. For indoor positioning a cascaded Extended Kalman Filter (EKF) and Particle Filter (PF) architecture is proposed. The system uses stance phase detection and the available floor map to construct the measurement models for the KF and motion constraints for the PF respectively. For navigating in inland waterways it is shown how to benefit from context information fusion by inferring the operating condition of the Global Navigation Satellite System (GNSS). In this scenario, context based criteria are derived for the selection of the best position estimation amongst several positioning solvers running in parallel. This work presents the basics for context fusion in tracking applications, illustrating the theory with two application examples. The preliminary results already demonstrate a performance improvement compared to state-of-the-art approaches.**

Keywords - Context Awareness; Target Tracking; Bayesian Estimation, Information Fusion.

I. Introduction

During the last decade, context-aided data fusion systems have became widely adopted within several applications. The paradigm of enhancing the sensor fusion processes with available context information has become specially popular in domains such as ground target tracking, maritime surveillance and location-based services (LBS) and many others. The behavior of the targets and the characteristics of data sources are conditioned by the environment (like terrain type or weather conditions), logical procedures and even by their interaction with other entities. Thus, context is considered as a key ingredient to improve the overall tracking performance, adapting the functions and models to the actual needs of the application.

This work aims to overpass the limitations of navigation due to noisy sensors or the presence of non-Gaussian errors by integrating contextual information within the Bayesian estimation framework. For this purpose two relevant example applications are presented: pedestrian indoor localization and inland waterway navigation. In both cases, the context knowledge is formalized with static or dynamic variables, and it is integrated in the non-linear Extended Kalman Filter (EKF) and Particle Filter (PF) estimation algorithms.

For indoor navigation, an accurate and reliable location information is considered to be one of the fundamental components of ubiquitous computing and future LBS. Moreover, for professionals such as firemen or soldiers, being self-aware of their location can be a decisive factor in emergency response stages [1]. The provision of an accurate and reliable position information for pedestrians in indoor scenarios still constitutes a challenge for the research community, especially when the availability of the infrastructure such as WLAN cannot be guaranteed. In this work, the lack of a position reference is addressed by inferring knowledge from the environment information (in a form of map), which is used to improve the performance of classical inertial indoor navigation with foot-mounted sensors using a cascaded EKF-PF approach.

Inland waterway navigation is yet another example of an application which can be enhanced using context information. The European Commission has stated that the carriage of goods through inland waterways is the most climate-friendly and energy-efficient approach, heartening companies to use this mean of transport in their operations [2]. Inland waterway applications include scenarios where pure satellite-based navigation becomes far more challenging compared to classical maritime applications with open sky conditions. This work proposes an architecture in order to exploit the context information, providing a robust position estimation even in case of poor quality of satellite signals.

The rest of the paper is organized as follows. Section 2 provides an overview of the state-of-the-art of context-based information integration, presenting the main strategy pursued when fusing situation awareness information. Section 3 briefly describes the main sources from which context can be exploited in tracking applications. In Sections 4 and 5 the two example applications are presented: indoor localization and inland waterway navigation, including both the description of the methods and the discussion of the results. Finally, Section 5 gives a summary and provides an outlook to future work.

II. Related Work

The vast bibliography on context-aided fusion can be organized from a functional point of view, as suggested in [3]:

A. Sensor Characterization

An intuitive example of an application in which the sensor performance strongly depends on the geographic context is the maritime radar. In multi-target tracking, the radar is typically used to discriminate between possible targets, as well as to separate the areas of poor coverage and to minimize the detection of false targets. Another common approach is to give a higher weight to sensors that are well-adapted to the actual context and to minimize the impact of those which are not. For instance, in Global Navigation Satellite System (GNSS) the measured carrier to noise density ratio is often used as a quality indicator: the stronger the received signal, the smaller the expected ranging error of this signal. Although some of the error sources cannot be discriminated by trivial signal strength analysis (such as non-line-of-sight (NLOS) or multipath effects), this or similar signal quality information can be extremely helpful in improving the accuracy of the position solution [4].

B. Target Prediction

Tracking algorithms may include the known traffic configuration (roads, channels, airways, etc) to improve the prediction model used within the estimation process. Automotive navigation systems typically fuse the information from noisy sensors with map matching to accurately compute the location of a vehicle on a road [5]. Similarly, in maritime domain the vessel route information can be used to constrain the assigned channels accordingly to the drought category and water depth [6]. For ground tracking, the Interacting Multiple Model (IMM) has been widely employed [7]. The general idea of IMM is to combine the estimated target states of a bank of filters, each conditioned on different dynamic models, by assigning weights with respect to their current fit to the data. Other algorithmic approaches to exploit context can include the modifications of PFs, where the samples of the target state are restricted and thus are drawn exclusively from the subspace generated by the geographic file [8].

C. Data Association

Context can also be used in the data association process to decide how many targets are in the scene and within the observation association. Joint Probability Data Association (JPDA) filters have been extended to use context in the form of external probabilities within the association process. In [9] the authors have identified different probabilistic data association methods, while the work in [10] has explored data association techniques for a multi-target tracking problems.

D. Track/Algorithm Management

Finally, the track management may also exploit the context to improve the fusion process in accordance to the situation. For instance, feedback strategies such as commands flowing from contextual situation level to the data fusion node can yield improvement in adverse conditions, such as high traffic or heavy clutter scenarios with small probability of target detection. Other options may include the automatic tuning or the selection of algorithms (multi-algorithm fusion) based on external input [11].

III. Context Exploitation

As mentioned above, the context can be considered as one of the essential components in the process of information fusion, aiding the refinement of the observations or confining the fusion process itself. Regarding the type of information used as context, several cases can be distinguished such as geographic data fields (e.g. geographic information system (GIS) or bathymetry records), motion constraints represented as roads or surface restrictions and dynamic context variables or domain closed-world knowledge.

A. Physical Context

Physical context represents one of the most direct uses of context in tracking applications. It is quite usual to represent the geographic data in the format of GIS files with terrain elevation or maritime information (coastline, bathymetry, etc). The same information has been also applied in the field of navigation [12] with terrain-aided positioning. Maps are usually represented as sets of waypoints and junctions to describe the road layout. The possibility of constraining the estimation process has been approached by different researchers both in ground and maritime domains [13]. As walls and other structures naturally restrict the motion of pedestrians, some authors [14], [15] employed the known floor maps to build motion models for the indoor navigation.

B. Logical Context

Target dynamics can also depend on the tactical or procedural information. For instance, motion on the road subject to velocity limits could often result in almost constant distances between the vehicles [16]. The same same applies to vessels, which mainly follow the known sailing plan and established shipping routes. Context can be made available by different means such as static data files, data services, human observers, inference processes, etc. Therefore, the context is not necessarily static information but it may appear as context variables that can influence the value of problem variables. The context should be collected and updated to be usable by the fusion processes and conveniently preprocessed to keep an updated and consistent repository of the relevant contextual information. Thus, the fusion should include an adaptation logic taking these contextual inputs into account in order to trigger the appropriate adaptation mechanisms (parameters, algorithms, control flow, etc). An in-depth analysis of the relevant strategies for logical context exploitation is proposed in [17].

IV. Pedestrian Indoor Navigation

We will start the discussion on practical approaches for context information fusion by presenting a challenging problem of indoor positioning. A common approach for pedestrian tracking is to employ a so-called Pedestrian Dead Reckoning (PDR) which measures the change in position/heading. This increment is then added to the previous pose to estimate the current location of the target [18]. The acceleration and angular rate from an Inertial Measurement Unit (IMU, 3-axis accelerometer and 3-axis gyroscope, often supported by 3-axis magnetometer for heading stabilization) are integrated to estimate the attitude, velocity and position change of the user. The most commonly used basis for navigation is the Bayesian estimation framework as it incorporates all the available information (uncertainties, noise statistics, kinematic constraints) in a statistically consistent way. Due to the nonlinear nature of the inertial-based navigation, for this work an EKF was adopted. The EKF, together with the Unscented Kalman Filter (UKF), can be considered as one of the most popular nonlinear modifications of the classical KF and are often used in navigation and tracking applications.

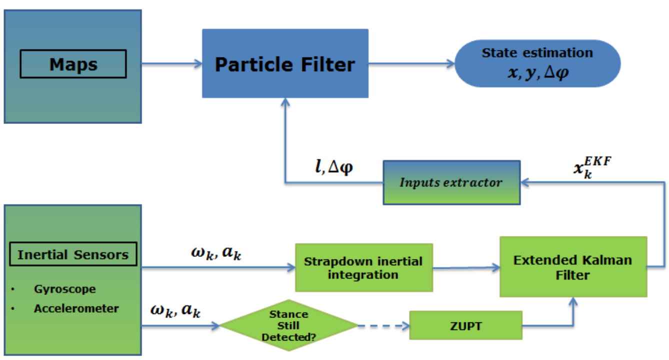

Fig. 1. The proposed cascaded architecture with inertial-based EKF and PF based on the map information and the extracted step length and incremental heading from the EKF.

Unfortunately, applying constraints to the estimated state within a classical KF is a non-trivial task [19]. In contrast, PF has been widely adopted for navigation applications due to its suitability to incorporate the constraints in an intuitive way. For the given application a cascaded KF-PF architecture is proposed, where the data from inertial EKF is fused with the map-induced motion constraints within the PF. The proposed system employs an IMU mounted on the shoe, with the inertial sensor data provided at a high sampling frequency (100 Hz). The EKF fuses the sensor data to estimate the pose of the foot, while the stance phase detector is used to determine the steps based on the accelerometer and gyroscope signals using experimentally obtained thresholds. Whenever a new step is detected, the step length and the heading change from the EKF are extracted and fed to the second stage PF. The latter uses the floor map information to enforce the motion constraints on the particles. In Fig. 1 the architecture of the proposed system is provided.

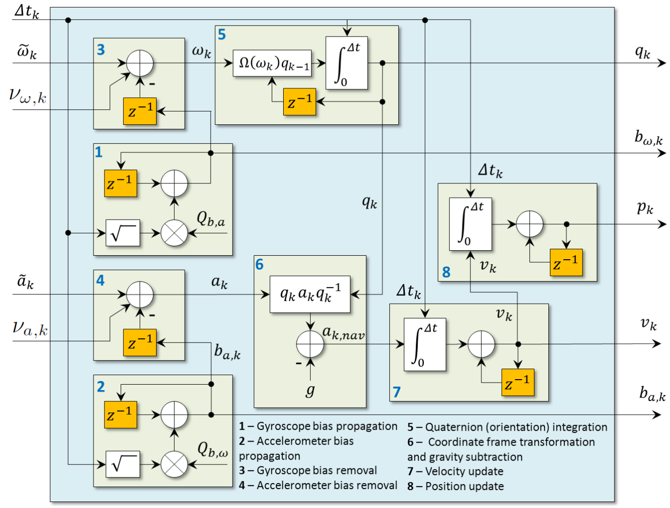

Fig. 2. A sketch of the process model for the prediction step in the EKF.

The state of the proposed EKF is defined as follows:

$$x_k = \left[q_k^T \; v_k^T \; p_k^T \; b_{w,k}^T \; b_{a,k}^T\right]^T \tag{1}$$

where $q_k \in \mathbb{R}^4$ represents the attitude (unit) quaternion, $v_k, p_k \in \mathbb{R}^3$ are respectively the velocity and the position, and $b_{\omega,k}, b_{a,k} \in \mathbb{R}^3$ represent the biases of the gyroscope and the accelerometer. Fig. 2 illustrates the process model which is basically a form of the classical strapdown inertial mechanization with several simplifications done to account for the poor performance of low-cost MEMS inertial sensors.

Due to the triple integration of noisy sensor measurements, in the absence of an external positioning reference, the classical inertial mechanization result in a position error growing cubically in time. In order to limit the position error growth to be only linear in time, a so-called ZUPT (Zero Velocity Update) [20] is applied as measurement model. Whenever the beginning of the midstance phase of a step is detected, the measurement model is triggered. ZUPT assumes that during the stance phase the velocity of the foot is zero, the corresponding angular rate is dominated by the gyroscope offset and the measured acceleration is due solely by a superposition of the Earth gravity and the accelerometer offset. Thus, the IMU bias corrections can be computed even without modeling the angular rate and the acceleration as part of the state vector.

The ZUPT mechanism itself is a distinct example of the context information fusion. It exploits the *a priori* knowledge that the sensor is placed on the shoe (foot) and, therefore, it is expected to be in the stance phase on a relatively regular basis. In this case, the context information allows the creation and application of so-called *pseudo-measurement* models without corresponding sensor hardware.

The PF is a Monte Carlo method which solves the filtering problems using a random state (hypothesis) sampling. The probability distribution function of the state is represented by N_s particles and their associated weights $\{x^i, w^i\}_{i=0}^{N_s}$. The particles are propagated based on the displacement and the

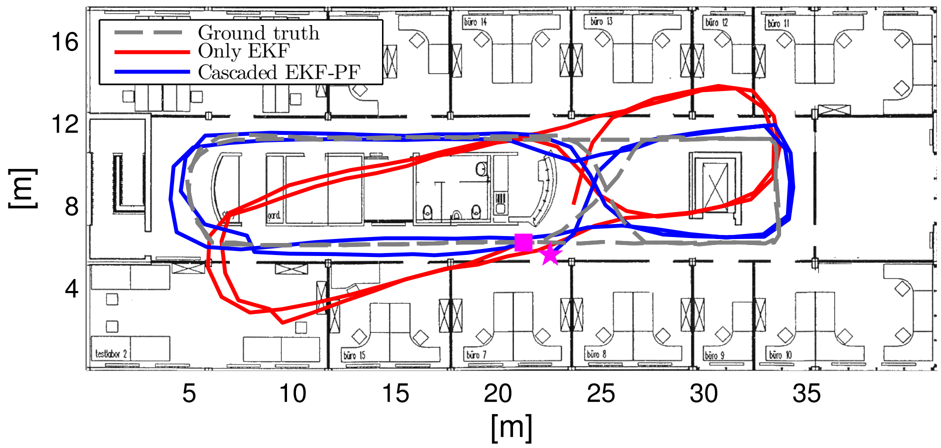

Fig. 3. User walking around an office following an 8-shaped trajectory and then returning to the initial position. The pink square and the pink star represent the initial position and the final estimated position respectively of the cascaded EKF-PF. The dashed gray line is the approximate original trajectory followed by the pedestrian, the red line represents the estimated trajectory by the EKF, and the blue line is the output of the cascaded EKF-PF localization system.

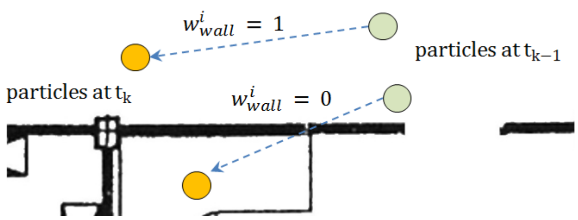

Fig. 4. An example of how the values of the weights $w^i_{wall,k}$ are determined.

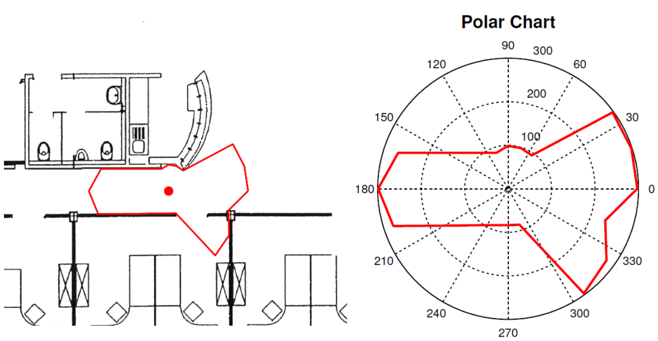

Fig. 5. The floor-map with the estimated mean position and the heading constraints (left) and the corresponding polar chart with the most likely directions (right).

incremental heading provided by the associated EKF. The Gaussian noise with the corresponding statistic to that in the EKF data is added both to the step length and heading change estimation to avoid particle depletion effects. Finally, the map information is exploited by weighting all the particles based on wall/obstacle detection and their direction of motion. The weighting factor for every particle is presented as a combination of two criteria:

$$w^i_k = w^i_{wall,k} \cdot w^i_{\varphi,k} \tag{2}$$

with $w^i_{wall,k}$ accounting for the particle having crossed any wall or obstacle. It is set to 0 if the path followed by the i^{th} particle violated any map constraint or to 1 otherwise (see Fig. 4). The weight w^i_{φ} reflects the likelihood of a particle moving in the direction of its heading. To compute this likelihood, a circle with radius $r = 3$ meters around the previously estimated mean position (centroid) is considered. Then, for every angular segment $\gamma = 9°$ of the circle, the minimum distance between the center and the wall is calculated. The larger the distance (r being the upper bound), the higher the weight assigned to a particle heading in that direction. The method eliminates less probable motion directions as it is assumed to be less likely for the user to approach the walls. Fig. 5 provides a rough sketch of the idea of this approach. Finally, a classical resampling step is performed with the final estimate calculated as a weighted sum of the particles.

The performance of the proposed system was evaluated by carrying out several experiments, in which a pedestrian walked in an indoor scenario equipped with a commercial well-calibrated IMU (XSens MTw) mounted on his foot. For the demonstration of the systems's performance, the user is asked to walk around an office following an 8-shaped trajectory and then to return to the initial position (see Fig. 3). Although the generic EKF approach already performs reasonably well and preserves the general shape of the trajectory (the estimated trajectory by the EKF is slightly rotated as the initial heading was not accurate), the estimated position would eventually drift if no reference information was provided. For the cascaded EKF-PF architecture, the estimated path not only becomes more accurate, avoiding the violation of any map constraints, but also results in a stable position over longer time. Note that the results are presented for a pure inertial approach and the associated map constraints are the only source of the complementary information for this indoor positioning system. For further information about the presented system as well as additional experiments, please refer to [21].

V. Inland Waterway Navigation

In the previous section we explored some potential ways to incorporate physical and logical context to the pedestrian indoor navigation application. Next, a novel technique to benefit from the environment perception in inland waterway navigation is presented. For target tracking a non-inertial constant velocity model KF is used. In the correction step, the KF is fed with the position solution from a code-based snapshot algorithm (strategy commonly denoted as *loosely-coupled* architecture). In this application, the knowledge of the GNSS operational condition, the map boundaries and the characterization of the vessel dynamics constitute the context information. This data is fused to constitute a measure of the quality for the position solution while using different solvers. The architecture for the proposed system is illustrated in Fig. 6.

Despite being the main source of information for navigation in maritime applications, the performance of the GNSS can be easily disturbed due to space weather events, jamming or multipath effects. The classical code-based positioning problem consists of solving a nonlinear Least Squares (LS) problem. Although widely adopted, the LS is known for lacking robustness as a single measurement outlier could introduce large errors in the position estimation. To cope with this problem, there have been several proposals to perform Fault Detection and Exclusion (FDE). For instance, in aviation the Receiver Autonomous Integrity Monitoring (RAIM) algorithms constitute the standard for FDE. Unlike aviation, in inland waterway navigation open-sky conditions barely occurs and the single fault assumption of classical RAIM limits the performance of these algorithms in scenarios with multiple possible faults.

Recently, several algorithms belonging to the statistical robust estimation framework have been proposed as an alternative to RAIM-based techniques. Among the different methods, Least Median of Squares (LMS) and GM estimator can be named as the most promising applied for positioning. So far there has been no clear statement on which of the robust positioning approaches can be considered as the best performing method. This can be, at least to some extent, attributed to the fact that the robust schemes often present complementary characteristics in terms of their Gaussian efficiency (i.e., similarity to classical LS under optimal Gaussian noise conditions) and the breakdown point (i.e. the smallest percentage of contaminated data that can cause the estimator to take on arbitrarily large aberrant values [22]), and, therefore, their ranking in performance could strongly depend on details of the application.

This work demonstrates how the context information can be exploited by constructing attributes which are subsequently used as the criteria within a multi-criteria decision making (MCDM) framework. While running several positioning algorithms in parallel, it is feasible to choose the best performing method out of the set based on how this particular solution matches the information induced from the context. For this

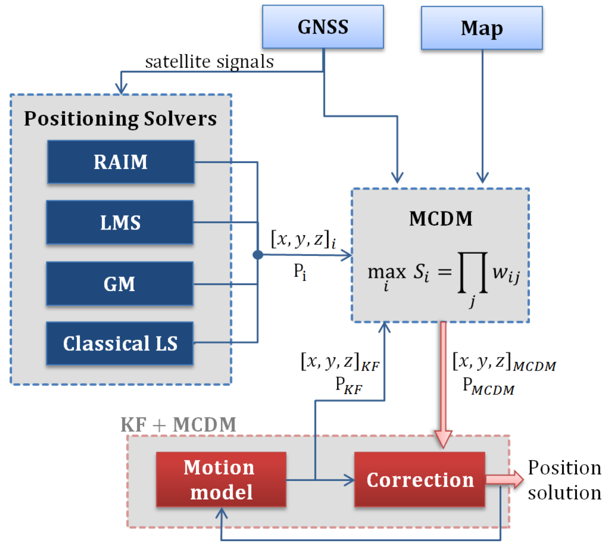

Fig. 6. Proposed architecture for enhancing navigation with context-based information. Different snapshot positioning solvers estimate a position solution in parallel and the best fitting solution is passed to the correction step of the loosely-coupled KF.

application, the MCDM problem is expressed as the maximization of the following product:

$$\max \; S_i = \prod_{j=1}^{J} w_{ij} \tag{3}$$

where S_i represents each of the eligible solvers: classical LS, LMS, GM estimator or RAIM. Here, w_{ij} corresponds to the values of each of the J attributes for the i^{th} positioning solver. Three attributes were derived:

- *Regular/abnormal operational condition*. The residuals of the measurements employed in the LS estimation can be studied within a χ^2-test with $n-4$ degrees of freedom (where n is the number of satellites available) to detect whether the assumption of normally distributed data is valid. LS is optimal under Gaussian conditions, while the other solvers are more appropriate under abnormal conditions when one or more outliers are present. Therefore, for regular operating conditions a weight of 1 is assigned to the LS output and 0 to the remaining solvers and vice versa in case a global inconsistency in LS solution is detected.
- *Violation of boundaries*. From the *a priori* knowledge of the scenario topography, as well as of the dimensions of the tracked vessel, one can deduce whether there is a violation of the boundaries (map). If the position estimated by a solver implies crossing a physical obstacle, the aforementioned solver is given a zero value for this attribute. For instance, if the position solution of a method indicated that the target would cross the pillars of a bridge, then the weight for that method would be set to 0, as it is providing false information.

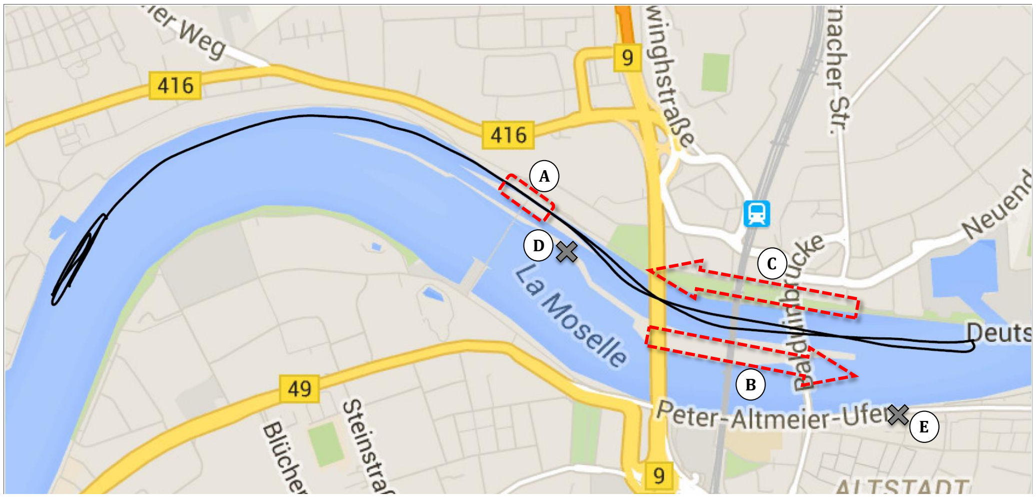

Fig. 7. Measurement track on the river Moselle near Koblenz (Germany). Reference path (black line) and several challenging segments including the lock (A), and 3-bridge segments (B) and (C). (D) and (E) indicate the places where the total stations were installed in order to obtain an accurate horizontal position reference of the vessel's path. Total trajectory duration - 1 hour. Image produced using Google Maps API.

- *Innovation test*. The residuals of the KF, meaning the difference between the predicted position and the estimated solution from the positioning solvers, are taken as the corresponding integrity indicators. The failure of the innovation test indicates that the corresponding positioning technique was heavily influenced by the contaminated satellite signals, and consequently, its solution can be rejected (weight equals to 0). On the other hand, the method whose solution passes the test has a weight equal to the inverse of the Bhattacharyya distance (a measure of the similarity between the two probability distributions).

As mentioned earlier, the position solution of the method maximizing the product of Eq. 3 is fed as an observation for the correction step of the KF. Hence, context-aided information has been used in this application as a way to weight the quality of the position solvers, choosing the most appropriate algorithm depending on its consistency with other information available.

To show the benefit of the proposed scheme, three different KF based implementations will be compared in the following:

- KF-LS. It uses the position estimated by a regular LS as observation, independently of any other information provided by the context or alternative solvers.
- KF-LS*. It employs solely the position solution from a regular LS. Unlike KF-LS, the context-information is applied as a mechanism to discard observations when they are not reliable (in case of the boundaries violation or not passing the innovation tests).
- KF-MCDM. The context information is fully exploited using the MCDM formulation stated before.

The performance evaluation of the presented system is conducted using real data from a measurement campaign that was carried out on the Moselle river in Koblenz (Germany). The river is considered as one of the busiest inland waterways in Germany and it represents a distinct challenge for the satellite-based navigation due to the presence of high structures, bridges, etc. The three bridges and the waterway lock constitute an environment in which the GNSS signals get strongly contaminated with multipath and NLOS effects. In this experiment, the research vessel "MS Bingen" was employed, equipped with three GNSS antennas, Javad Delta receivers and a reflector cylinder (used in conjunction with two total stations to accurately track the reference trajectory). For one hour, the vessel performed an 8-shaped trajectory, with several passes under the bridges and the waterway lock, as shown in Fig. 7.

Despite providing an accurate positioning for the most part of the trajectory, the classical code-based LS dramatically fails in the vicinity of the bridges. The horizontal position errors exceed 50 meters due to the lack of robustness against the errors that are present in the satellite signals. Even though the robust schemes reduce the maximum position error by more than 15 meters in comparison to the classical LS technique, the errors under the bridges are still large enough to consider the position solution as not reliable. The presented strategy allows the exploitation of the context-induced information as a mean of distinguishing the operating conditions and selecting the most suitable GNSS positioning solver for every situation.

The Table I shows the obtained error statistic and provides a solid proof of the benefits brought by the use of the context-based information. For completeness of the study, the individual performance of each of the code-based GPS L1 positioning solvers is also provided in Table I.

The position solutions from the snapshot methods and the KF-based implementations are compared against the position reference coming from two optical total stations. As we can see in the first half of the table, the Horizontal Position Error (HPE) of the robust methods and RAIM is highly reduced compared to that of the regular LS. However, it is difficult to point out which is the best performing method overall,

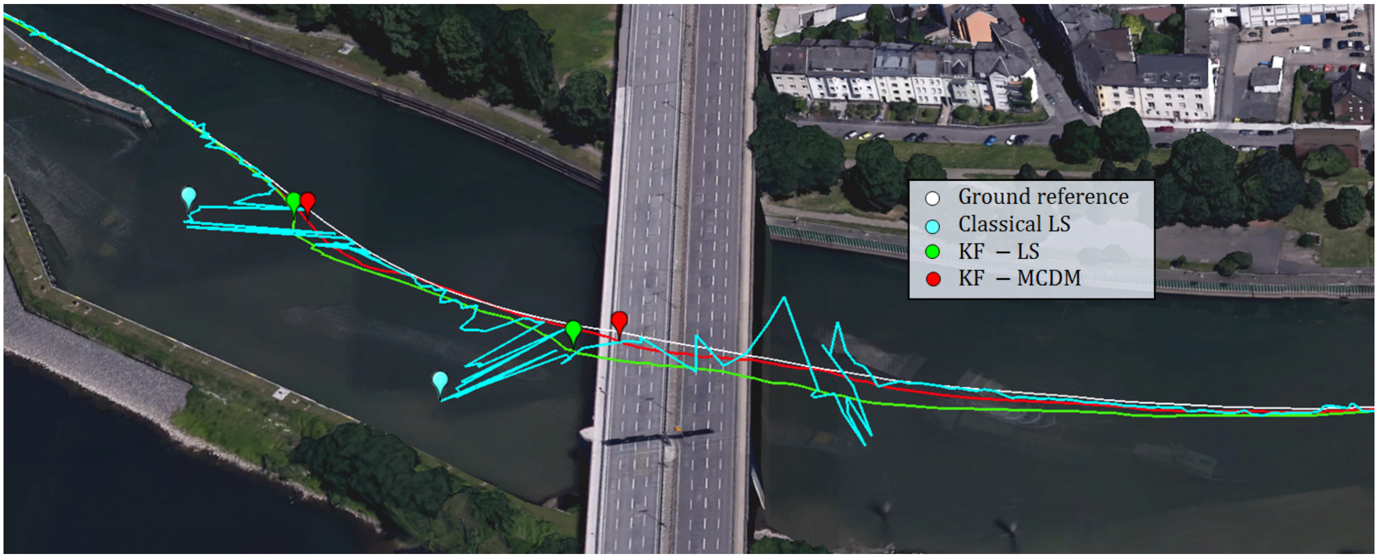

Fig. 8. Positioning performance of the regular LS and the different KF implementations: KF-MCDM and KF-LS. Background figure from Google Earth.

TABLE I
PERFORMANCE COMPARISON OF THE CODE-BASED POSITIONING SOLVERS AND THE KALMAN FILTER IMPLEMENTATIONS

Method	Mean HPE [m]	RMS HPE [m]	Max HPE [m]
LS	2.9	4.5	50.7
LMS	2.4	3.4	34.9
GM	2.3	3.2	35
RAIM	2.3	3.0	45.4
KF-LS	3.0	3.8	17.8
KF-LS*	2.8	3.3	13.0
KF-MCDM	2.5	2.9	10.4

especially because the error characteristics of the methods can be often considered as complementary.

Concerning the performance of the KF, although no improvement is obtained in terms of mean HPE, the maximum position errors are significantly lowered when compared to the memoryless (snapshot) positioning algorithms. One could assume that this reduction is mostly related to the smoothing behavior of classical KF due to process dynamics assumptions. However, by exploiting the context-induced information in the KF-MCDM the maximum HPE could be improved by another 7m compared to the standard KF-LS approach. Furthermore, the use of different positioning solvers in MCDM becomes fully justified and highly beneficial as it brings an improvement of more than 30 cm and 2 m in the mean and maximum position errors respectively (when compared to the KF-LS* approach).

Note that the suggested MCDM architecture also allows rejection of all position solvers if they do not satisfy the three criteria. Moreover, the consistency of KF is ensured by imposing a maximum five second period during which none of the GNSS solvers is used as measurement update. If during this time none of the methods was selected, the innovation test condition is disabled in order to bound the position error drift within the KF.

The differences between the KF-LS and the KF-MCDM are also illustrated in Fig. 8. In the vicinity of the bridge the position estimated by the LS algorithm is strongly affected by NLOS or multipath effects. The knowledge that the GNSS receiver is probably operating under abnormal conditions is inferred from the consistency of actual measurements and the KF-MCDM is able to use the position solutions of the snapshot solvers (such as RAIM or LMS) which are more robust against the outliers. While the regular KF follows the incorrect position reference of the classical LS solver, the suggested KF-MCDM approach can also detect that there is, probably, no reliable position solver at all and is able to completely ignore the GNSS-based reference while relying on the assumed motion model for shorter time.

VI. Summary and Outlook

The work presents the basic concept of fusing context-aided information in tracking applications while providing an overview of the most frequently applied techniques. The main goal of this work is to demonstrate the improvement gained by integrating contextual information within classical navigation techniques for two challenging scenarios. The knowledge inferred from the environment is treated as if it was an additional sensor, becoming a powerful tool to improve the overall performance of the navigation solution. Two example applications are presented and the potential benefits of the context information fusion are manifested.

For indoor navigation, a cascaded architecture is suggested, where the EKF performing classical strapdown mechanization is used together with a PF. Firstly, the fact that the IMU is mounted on the foot of the user allows the construction of a ZUPT measurement models for the EKF. These models are used to reset the estimated drift whenever a new step is detected. Then, a PF uses the estimation from the EKF and the floor map information to impose motion constraints via an adjustment of the weights of the particles. The performance of the system is evaluated using real measurements recorded with an user walking through a typical office building.

For the inland waterway navigation example, the context information is extracted to create a set of attributes to rate the quality of different positioning solvers running in parallel. The knowledge from the environment is inferred in several ways. First, the consistency of the residuals of LS solution allows the algorithm to asses whether regular or abnormal operating conditions are present. Second, the map of the scenario can be exploited to detect whether the estimated position is violating the boundaries of the river or pillars of the bridges. Finally, the prediction of the state from the KF is compared to the position solution from the solvers using the position innovation test. This test allows the KF to reject the position measurement if the mismatch between the predicted and the measured positions is too large. The experimental results provided in the second example clearly demonstrate how the inclusion of the context information can improve the performance of the navigation system under unfavorable GNSS conditions.

Further work is planned in formulating the indoor positioning problem using more efficient Rao-Blackwellized PF as well as in handling the context for multi-modal distributions. In the case of the inland waterway navigation, it is planned to extend the framework for multi-antenna and multi-constellation systems as well as to include GIS data such as bathymetric data.

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